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Using Neural Network, Human Recognition based on Hand Geometry Method using Fractional Local Ternary Intensity Pattern (FLTIP) Model

Dr. Shreenidhi.P.L,,
Dept of Information Technology,
UTAS-MCT

Ms. Shaima Al Hashmi,
Dept of Information Technology,
UTAS-MCT

Dr. Hemalatha Jai Kumari,
Dept of Information Technology,
UTAS-MCT

***Abstract*—Hand geometry feature based image classification is one of the interesting research area in the field of biometric recognition and authentication systems. This type of recognition system is deployed in many applications for ensuring the secure authentication, person identification, and access control. For this purpose, some of the image processing techniques have been developed in the existing works, but it limits with the issues like reduced accuracy, classification efficiency, and increased error rate. In order to solve these problems, this paper intends to develop a new pattern extraction based classification technique for hand geometry feature recognition. At first, the input test image is preprocessed by using the Windowed Convolution Gaussian Filtering (WCGF) technique for eliminating the noise pixels and smoothening the image. After that, the block separation is performed for extracting the most useful patterns from the filtered image with the use of Fractional Local Ternary Intensity Pattern (FLTIP) technique. Consequently, the Neural Network (NN) classifier is implemented to recognize the image based on the extracted feature vectors. During experimental analysis, the performance of the proposed technique is validated by using various evaluation measures. Also, it is compared with some other existing techniques for proving the superiority of the proposed pattern extraction based classification system.**

Index Terms*—*Hand Geometrical Features, Windowed Convolutional Gaussian Filtering (WCGF), Fractional Local Ternary Intensity Pattern (FLTIP), Neural Network (NN) Classifier, Biometric Authentication, and Recognition System.

I. INTRODUCTION

BIometric authentication and recognition is one of the emerging research area in the recent days for ensuring security [1,2] . A biometric system is a kind of pattern recognition system, where a biometric data of a person can be operated based on the set of characteristic extracted from the dataset [3]. Typically, the authentication can be performed based on the physiological and behavioral features for personal recognition. The characteristics like face, iris, fingerprint, and veins are the kind of physiological biometrics. In which, the hand biometrics are the most suitable option for authenticating the valid person based on an access control mechanism [4, 5]. Moreover, the hand geometry based authentication is termed as a standard level identification system, which satisfies the most suitable and required characteristics for authentication. In most of the biometric recognition systems, the image is considered as the suitable source for analyzing the features and other parameters required for authentication [6, 7].

Generally, the human hand comprises an extensive range of characteristics that could be processes or operated by the use of hand geometry biometrics [8]. Based on the utilization of image acquisition device, it is categorized into the types of constraint and unconstrained contact based methods. Moreover, ensuring the security and user integrity are highly essential for protecting the privacy information against the unauthenticated access. For this purpose [9], many biometrics based authentication mechanisms have been developed that protects both the user's privacy and security. A typical hand geometry biometrics system have following stages: pre processing of image, segmentation, feature updates, optimization, and classification [10]. Based on these processes, the authenticated person can be identified by using the hand geometry biometrics. Most of the traditional works developed a hand geometry features based biometric authentication system for ensuring the individual person security. But, it lacks with some issues like increased computational complexity, time consumption, reduced accuracy, recognition performance and inefficient classified results. In order to solve these issues, this paper intends to develop a pattern based classification system for hand geometry image processing. Here, the geometrical features are considered to represent the person identification and classification. The major objectives focused on this work are listed as follows:

- To remove the noise and artifacts in the input hand image, a new preprocessing technique named as, Windowed Convolutional Gaussian Filtering (WCGF) is developed.
- To extract the most required patterns used for authenticating the person, a Fractional Local Texture Intensity Pattern (FLTIP) is proposed.
- To classify the image with increased recognition rate based on the geometrical features, a Neural Network (NN) technique is utilized.

The rest of sections present in this paper are structured as follows: the existing algorithms related to preprocessing, feature extraction, and classification used for hand geometry image processing are surveyed in Section II. The complete performing description about the methodology proposed with its overall flow illustration are stated in Section III. The results of experiment and comparing both existing and proposed classification techniques are validated using various measures in Section IV. Finally, the paper is concluded with its future enhancements in Section V.

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II. RELATED WORKS

This section surveys the existing techniques related to the hand geometry verification and classification based on its features.*Prabu, et al* [11] suggested a Hybrid Adaptive Fusion (HAF) technique for improving the accuracy of biometric recognition system. The main intention of this paper was to develop a secure identification and authentication system based on the iris of users. For this purpose, different feature extraction techniques such as Scale Invariant Fourier Transform (SIFT) and Linear Binary Patterns (LBP) were utilized in this work. Also, the median filtering technique was used to eliminate the noise and irrelevant features in the input iris images. In order to exactly classify the verified users, an extreme machine learning algorithm was employed. *Bahmed, et al* [12] introduced a multimodal biometric system for a secure personal authentication and access control. The major stages involved in this system were, image extraction, orientation, key point localization and feature extraction. Here, the feature selection based finger geometry was performed to eliminate the redundant information and to increase the accuracy of prediction. Then, the recognition could be performed to select the optimal features with low correlation. The main benefit of this technique was, it provided an increased accuracy and efficiency by incorporating the geometric features with extra biometric features.

Ghose, et al [13] suggested a new feature descriptor algorithm based on the neighborhood intensity pattern for an efficient image retrieval process. Here, an isotropic Gaussian filtering technique was applied to increase the robustness of the mechanism based on multi-resolution analysis. Moreover, the retrieval performance could be improved with the help of Genetic Algorithm (GA). *Jaswal, et al* [14] recommended an adaptive histogram equalization method for ensuring the security of multimodal biometric authentication system. Here, a palm print and hand geometry features have been considered to increase the accuracy of classification. The stages comprised in this work were as follows: ROI extraction, feature extraction and geometry recognition. In order to improve the overall performance of recognition, a fusion of hand shape, palm print and geometrical features have been extracted from the given image. In paper [15], the hand geometry measurements have been used for improving the accuracy of biometric authentication system. Here, 12 different features were utilized to accurately authorize the persons in a hand recognition system. The study done in this research were acquisition of image, preprocessing, and feature expansion. Moreover, the personal authentication could be performed geometrical features extracted from the input image. The disadvantage behind this work was, it required to increase the accuracy of classification.

Song, et al [16] introduced a multi-touch authentication mechanism by incorporating the hand geometry and behavioral characteristics information. The benefits of this mechanism were simplicity, efficiency, security and usability. The intention of this technique was to improve the accuracy of user legitimation with better reliability. *Sagayam and Hemanth* [17] surveyed various hand geometry feature and recognition technique for selecting the most suitable classification algorithm to biometric authentication system. The major objectives have been focused on this study were to reduce the computational complexity, error rate, then to improve the classification rate and susceptibility. Here, both the supervised and unsupervised machine learning algorithms have been validated to analyze the efficacy of the suitable mechanism used for hand geometry feature recognition. *Angadi, et al* [18] suggested a multiclass Support Vector Machine (SVM) technique for increasing the performance of hand geometry system. Here, the complete connected graph was utilized to increase the identification rate with reduced complexity. Also, the spectral properties have been utilized for a peg-free hand geometry based user authentication system. The stages involved in this system were preprocessing, segmentation, graph representation, feature extraction, and classification.

Jaswal, et al [19] utilized a palm print and hand geometry features for developing a secure multimodal biometric authentication system. Here, the local texture and geometrical patterns have been extracted for increasing the accuracy of classification. Moreover, Fisher Linear Discriminant (FLD) analysis method was utilized for optimal projections on the image. At last, the SVM based classification and fusion techniques were employed to exactly recognize the objects. In paper [20], an improved Bacterial Foraging Optimization (BFO) was developed for a hand based biometric authentication system. In this system, three types of biometrical features such as finger print, palm print and finger inner knuckle print have been considered for segmentation. At last, the fusion was applied on these images by the use of Particle Swarm Optimization (PSO) method. *de Christo, et al* [21] employed a biometric authentication system, which comprised the stages of feature extraction, preprocessing, fusion and classification. Here, the SVM based classification technique was employed to accurately recognize the biometric patterns. In addition, a fusion method based on attributes was used to fuse the image by the use of geometrical features. Khaliluzzaman, et al [22] suggested hand geometry features based authentication mechanism for ensuring an increased security. The research involved in current system were preprocessing, color conversion, boundary extraction, and ROI estimation. In this analysis, it was stated that the performance of authentication system was highly depends on the feature vectors of the given images.

III. PROPOSED METHODOLOGY

This section presents the detailed description about the proposed hand geometry features based personal verification system. The major aim focused on this work is to improve the recognition accuracy of authentication based on the feature representation of the images. For this purpose, a novel techniques such as Windowed Convolution of Gaussian Filtering (WCGF), and Fractional Local Ternary Intensity Pattern (FLTIP) techniques are proposed. The overall flow of the proposed system is depicted in Fig 1, which includes the following stages:

- Preprocessing
- Block separation
- Pattern extraction
- Classification

Initially, the given testing hand image is preprocessed for normalizing the image with better smoothening rate, which is

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performed by the use of WCGF technique. Then, the blocks of the preprocessed image are segregated for extracting the patterns of the image, where FLTIP pattern is applied for extraction. It efficiently extracts the geometrical features for increasing the overall accuracy of classification. Finally, the NN classifier is employed to classify whether the person ID is authenticated or unauthenticated.

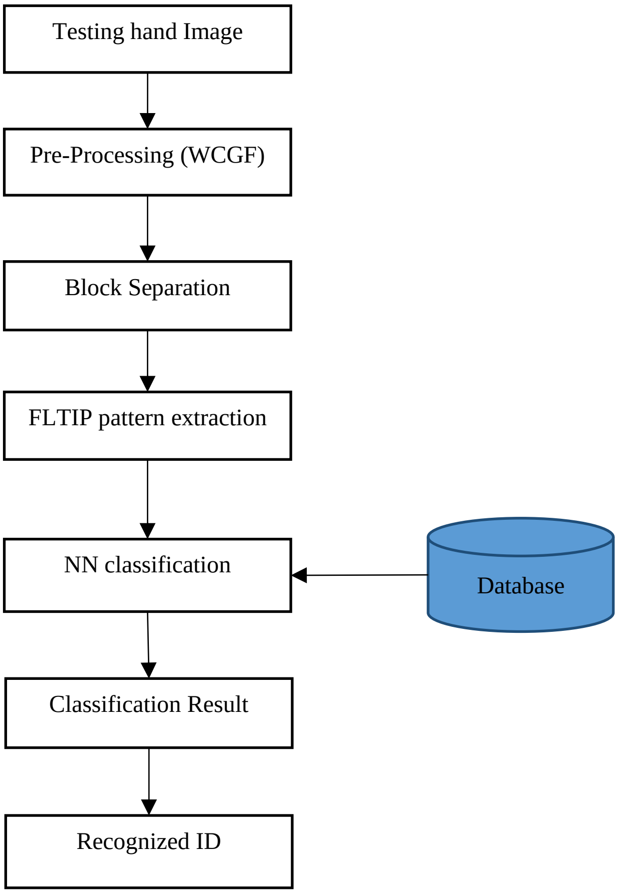

Fig 1. Flow of the proposed system

A. *Image Preprocessing*

Typically, the image preprocessing is one of the initial and important stage in any image processing applications. Because, it is essential to ensure the increased precision rate of the subsequent steps. Also, it reduces the impacts of artifacts that could affect the accuracy of classification. For this purpose, an efficient preprocessing technique, named as, Windowed Convolution of Gaussian Filtering (WCGF) method is utilized in this work. It filters the noisy pixels and enhances the edge details for obtaining a clear texture patterns for further processing. Moreover, it smoothens the image by applying normalization for eliminating an irrelevant and unwanted information. In this model, the noise can be represented as E_{xy} based on the following equation:

$$E_{xy} = \begin{cases} C_{ij}, & if\left(mean\left(T_{ij}\right) > I_{xy}\right) \\ 0, & Otherwise \end{cases} \quad (1)$$

Where, I_{xy} represented the image pixels for all x and y.
$x = \{1,2, \ldots M\}$; Where, M is the row size of image. $y = \{1,2, \ldots N\}$; Where, N is the column size of image. After getting the input image, the sharpening is performed by using the following equation:

$$I_e(x,y) = I_{in}(x,y) + \lambda H(x,y) \quad (2)$$

Where, λ defines the tuning filter parameter and $H(x,y)$represents the high pass filter mask. After that, the image is separated into cells based on the following equation:

$$T_{ij} = I_e(x-1{:}x+1, y-1{:}y+1) \quad (3)$$

Then, the average difference value inT_{ij} is computed with respect to the size of filter mask K and center pixel of the mask matrix I_c. Here, the index of mask matrix is represented as as shown in Fig 2. In which, the matrix size can be presented in both 3×3 and 5×5 matrix formats. The performance of filtering can be enhanced with respect to the minimum the size of mask. This type of filtering improves the value of peak signal to noise ratio value by performing the higher pixel reconstruction with the reduced number of noisy pixels.

i-1, j-1	i, j-1	i+1, j-1
i-1, j	i, j	i+1, j
i-1, j+1	i, j+1	i+1, j+1

(a). 3 × 3 matrix

i-2, j-2	i-1, j-2	i, j-2	i+1, j-2	i+2, j-2
i-2, j-1	i-1, j-1	i, j-1	i+1, j-1	i+2, j-1
i-2, j	i-1, j	i, j	i+1, j	i+2, j
i-2, j+1	i-1, j+1	i, j+1	i+1, j+1	i+2, j+1
i-2, j+2	i-1, j+2	i, j+2	i+1, j+2	i+2, j+2

(b). 5 × 5 matrix

Fig 2. Indexing of mask matrix for filtering

At last, the filtered output is taken as $I_f(x,y)$, which is further used for pattern extraction. The working procedure of the proposed WCGF technique is illustrated as follows:

Algorithm I – Windowed Convolution of Gaussian Filtering

Input: *Testing image* I_{in};
Output: *Filtered image* I_f;
Step 1: After getting the input image I_{in}, *the image sharpening can be performed as shown in equation (2) by using the tuning parameter and high pass filter mask.*
Step 2: for x = 2 to M-1 do
Step 3: for y = 2 to N-1 do //Where, M and N are image size.

Step 4: *Cell separation can be performed as shown in equation (3), and noisy pixel is estimated based on equation (2).*
Step 5: *The average difference value is computed in T_{ij} using equation (3).*
Step 6: *If, $I_g \sim I_c \sim I_m$ then*
$t = I_g$
Else
$t = I_c$
End if
Step 7: *The filtered is, $I_f(x,y) = t$*
Step 8: *end y loop;*
Step 9: end x loop;

B. Pattern Extraction

After preprocessing, the patterns of the filtered image are extracted by using the Fractional Local Texture Intensity Pattern (FLTIP) technique. It is also one of the essential stage for extracting the most relevant information that are used for characterize each class on the image. Here, the pattern extraction is mainly performed for increasing the overall accuracy and efficiency of classification. In this algorithm, the filtered image I_f is taken as the input for pattern extraction, in which the zero padding is initialized with two rows and two columns with respect to the overall boundary. Then, the window sizeI_W can be represented as the mask of 5×5 for extracting the patterns from the input. These image cells can be 5 different angles quantization of projection plane for the index of $\{+90^0, +45^0, 0^0, -45^0, -90^0\}$.

$$I_{\alpha_L}(x,y) = \sum_{x=-N_1}^{N1} \sum_{y=-N_2}^{N_2} |I_W(x,y)| \times f_1(\alpha_L, \alpha_U, r) \tag{4}$$

Where, $f_1(\alpha_L, \alpha_U, r) = \begin{cases} 1 & if\ \alpha_L \le \alpha_U < r \\ 0 & else \end{cases}$

$\alpha_L = \{+90^0, +45^0, 0^0, -45^0, -90^0\}, \alpha_U = \alpha_L - 45^0$ // 'r' is the size of mask matrix. From this index, the set of neighborhood pixels are extracted as α_k, which is computed as follows:

$$\alpha_k = \{I_M(i-1:i+1, j-1:j+1)\} \tag{5}$$

After that, the set of nearest neighborhood pixels are predicted from this boundary pixel collections with respect to the mean average value μ_k, which is estimated as follows:

$$\mu_k = \frac{1}{L} \sum_{a=1}^{L} \frac{|\alpha_k(a) - I_M(i,j)|}{I_M(i,j)} \tag{6}$$

Consequently, the average of same mean difference μ_c between the matrix center pixel is calculated from each boundary pixel, which is shown in below:

$$\mu_c = \frac{1}{L} \sum_{a=1}^{L} \frac{|\alpha_k(a) - I_c|}{I_c} \tag{7}$$

For each iteration, the mean values of μ_k and μ_c are computed based on its sign difference, which is used to extract the binary stream of the separated mask as shown in below:

$$S = \begin{cases} 1, & if(\mu_k > \mu_c) \\ 0, & Otherwise \end{cases} \tag{8}$$

After that, the corresponding decimal value of B is computed from the binary streams, which is represented as follows:

$$B = B + (2^{k-1} \times S) \tag{9}$$

Consequently, the maximum pixel progression for each pixel is estimated as γ_k shown in below:

$$\gamma_k(x,y) = \max_{\alpha_L}\left(I_{\alpha_L}(x,y)\right) \tag{10}$$

Then, the binary code mapping is performed for obtaining the pattern vectors from the input, which are illustrated as follows:

$$I_p(x-2, y-2) = B \oplus \sum_{i=0}^{P} 2^i \times f_2\left(I_{Ref}(s,t), I_{\gamma_1}(s,t), I_{\gamma_2}(s,t)\right) \tag{11}$$

Where, $I_{Ref}(s,t) = I_W(x+t, y+t), \quad \forall t = -1:1$

$$f_2(p,q,r) = \begin{cases} 1 & if\ p < r\ \&\ q > 0\ \&\ q > r \\ 0 & else \end{cases} \tag{12}$$

The detailed working procedure of the proposed FLTIP based pattern extraction is illustrated in Algorithm II.

Algorithm II – Pattern Extraction using FLTIP

Input: Filtered Image, I_f
Output: Texture pattern of the image, I_P
Initialize zero padding for convoluted image in 2 rows and 2 columns at the overall boundary for matrix I_f. $I'_f = I_f$
Initialize 'I_W' be the 5×5 window size represent as the mask for pattern extraction of the input image.
For x = 3 to m-2 **loop**
For y = 3 to n-2 **loop**
Let, $I_M = I_{\alpha_L}(x-2:x+2, y-2:y+2)$
Let,$I_c = I_{\alpha_L}(x,y)$
Initialize B = 0
L = (p*q)-1
For k = 1 to L**loop**
Collect the set of neighborhoods 'α_k' using equation (5)
Where, $i = 2\ to\ p-1$
$j = 2\ to\ q-1$.
Estimate 'μ_k' for each iteration of 'k' using equation (6).
Estimate 'μ_c' for each 'α_k' using equation (7)
Estimate sign change 'S' between center pixels and its boundaries as a logical output by using equation (8).
Calculate binary to decimal value 'B' for the binary stream of 'S' by using equation (9).
End loop 'k'
Calculate maximum pixel progression at each pixel by equation (10).
Binary code mapping by using equations (11) and (12).

$$\begin{cases}\gamma_k = 1 \rightarrow s = 1; t = 0 \\ \gamma_k = 2 \rightarrow s = 1; t = 1\end{cases}$$

End loop y
End loop x

i-2, j-2	i-1, j-2	i, j-2	i+1, j-2	i+2, j-2
i-2, j-1	i-1, j-1	i, j-1	i+1, j-1	i+2, j-1
i-2, j	i-1, j	i, j	i+1, j	i+2, j
i-2, j+1	i-1, j+1	i, j+1	i+1, j+1	i+2, j+1
i-2, j+2	i-1, j+2	i, j+2	i+1, j+2	i+2, j+2

(a) Estimate α_c

i-2, j-2	i-1, j-2	i, j-2	i+1, j-2	i+2, j-2
i-2, j-1	i-1, j-1	i, j-1	i+1, j-1	i+2, j-1
i-2, j	i-1, j	i, j	i+1, j	i+2, j
i-2, j+1	i-1, j+1	i, j+1	i+1, j+1	i+2, j+1
i-2, j+2	i-1, j+2	i, j+2	i+1, j+2	i+2, j+2

(b) Estimate α_k

Fig 3. Phasor diagram of FLTIP

Fig 3 depicts the phasor representation of FLTIP technique, in which the regonition of neighborhood pixels with respect to validation of different angles is illustrated. Here, the red colored block represents the pointer that can be used to estimate the value of α. If the index is at the center pixel of the matrix, the value of α_c is estimated and the neighborhood pixels at the coordinate position of (x, y) can be represented for computing the value of'α_k'. Then, the projection angles of the arrow indicates the estimation of magnitude of current matrix. In this case, the center pixel $\alpha_k$is not considered and the boundary pixel is not considered for 'α_c'. After extracting the patterns, the geometrical features are also extracted from the filtered image I_f. In this technique, the orientation of the image matrix θ is calculated and the image matrix can be rotated with respect to the updated angle for getting an accurate orientation, which are calculated as follows:

$$\theta = \frac{1}{2}\tan^{-1}\left(\frac{2\mu_{11}}{\mu_{20}-\mu_{02}}\right) \quad (13)$$

Where, μ_{ij} represents the central moments of the image, which is estimated as shown in below:

$$\mu_{ij} = \sum_i \sum_j \left(\left(I_f(x - x_\mu)\right)^i \left(I_f(y - y_\mu)\right)^j\right) \quad (14)$$

Where, x and y indicates the image coordinate matrix, and the value of x_μ and y_μ are estimated as follows:

$$x_\mu = \frac{I_f(1,0)}{I_f(0,0)} \quad (15)$$

$$y_\mu = \frac{I_f(0,1)}{I_f(0,0)} \quad (16)$$

Where, $I_f(0,0)$ is the central pixel of the image mask, $I_f(0,1)$ and $I_f(1,0)$ are the neighbor pixels for the angles of 0^0 and 90^0 respectively. After that, the image matrix can be rotated with respect to the updated for analyzing the correct orientation of the image matrix based on θ, which is shown in below:

$$\theta' = \begin{cases} 90 - \theta, & +90 \geq \theta \geq 0 \\ -90 - \theta, & -90 \geq \theta < 0 \end{cases} \quad (17)$$

Consequently, the upper peaks and lower peaks in the hand image is computed based on the finger tips and valley. Then, the vertices of the higher peaks and lower peaks are estimated based on the x and y coordinates of the image pixels. Based on these, the output geometrical key points F_V are extracted from the filtered image.

Algorithm III - Geometrical feature extraction

Input: Filtered Image, I_f
Output: Geometrical key points, F_V
Step 1: Estimate the orientation of image matrix 'θ' using equation (13)
Step 2: Rotate the image matrix for the updated angle to get the correct orientation of image matrix by using θ' as shown in equation (17)
Step 3: Estimate the finger tips and valley by checking the upper peaks and lower peaks in the hand edge image
For x = 2 to m-1**loop**
For y = 2 to n-1 **loop**

$$L = \sqrt{I_f'(x-1, y-1)^2 + I_f'(x, y)^2}$$

$$\theta = atan2\left(I_f'(x-1, y-1), I_f'(x, y)\right)$$

If($\theta > \theta'$), then
$V_1 = \{x, y\}$ // 'V1' represents the vertices of higher peaks and {x, y} are the co-ordinates of image pixels.
Else
$V_2 = \{x, y\}$ // 'V2' represents the vertices of lower peaks and {x, y} are the co-ordinates of image pixels.
End If

$$F_V = \{V_1, V2\}$$

End loop 'y'
End loop 'x'

C. *Classification*

After analysing the patterns, the Neural Network (NN) classification technique is employed for exactly classifying the recognized image. It performs multiple classification processes based on the image dataset. Here, the texture classification is mainly performed to improve the recognition process by estimating the network layer connectivity based on the dynamic range of neuron selection. Typically, the NN classification technique is used to classify the hand image patterns in the class of 0 or 1. This type of classification can

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efficiently improves the accuracy rate by using the patterns that are extracted in the previous stage. Here, the amount of input samples are trained and patterns are classified with increased accuracy rate.

IV. RESULTS AND DISCUSSION

This section evaluates the performance of the proposed hand geometry feature biometric classification system by using various evaluation measures. Also, some of the existing mechanisms have been considered for comparing the performance values. In this analysis, the NTU hand digit dataset, HKU hand geometry feature dataset, HKU multi-angle hand geometry feature dataset, La-RED dataset and MU-Hand image-ASL dataset are taken for validating the performance results. In which, the NTU dataset contains 1000 sample images if 10 hand postures, that are gathered from 10 different cases. Then, the HKU dataset contains 10 hand postures of 5 subjects, where 1000 cases are exist in this dataset. The ASL dataset contains 700 images of 10 different postures and LaRED dataset comprises 243,000 samples of 10 subjects.

A. Performance Indicators

The commonly used measures for evaluating the results of image classification system are sensitivity, specificity, jaccard, dice, precision, recall, F1-measure, Matthews Correlation Coefficient (MCC), and error rate, kappa coefficient, and accuracy, which are calculated as follows:

$$Sensitivity = \frac{TP}{TP+FN} \tag{18}$$

$$Specificity = \frac{TN}{TN+FP} \tag{19}$$

$$Jaccard\_Similarity = \frac{TP}{TP+FN+FP} \tag{20}$$

$$Dice\_Overlap = \frac{2TP}{FP+2TP+FN} \tag{21}$$

$$\Pr ecision = \frac{TP}{TP+FP} \tag{22}$$

$$\operatorname{Re} call = \frac{TP}{TP+FN} \tag{23}$$

$$F1\_Score = \frac{2\times \Pr ecision \times \operatorname{Re} call}{\Pr ecision + \operatorname{Re} call} \tag{24}$$

$$MCC = \frac{TP\times TN - FP\times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \tag{25}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{26}$$

$$Error\_Rate = 1 - Accuracy \tag{27}$$

$$Kappa\_Coeff = \frac{P_o - P_e}{1-P_e} \tag{28}$$

Where, TP – True Positive, TN – True Negative, FP – False Positive, FN – False Negative. Fig 4 and Table 1 compares the values of sensitivity, specificity, precision, F1-score and MCC of both existing [23] and proposed techniques. From the evaluation, it is analyzed that the proposed technique provides an increased performance values, when compared to the existing technique. Because, it efficiently extracts the patterns by using FLTIP and geometrical feature extraction technique.

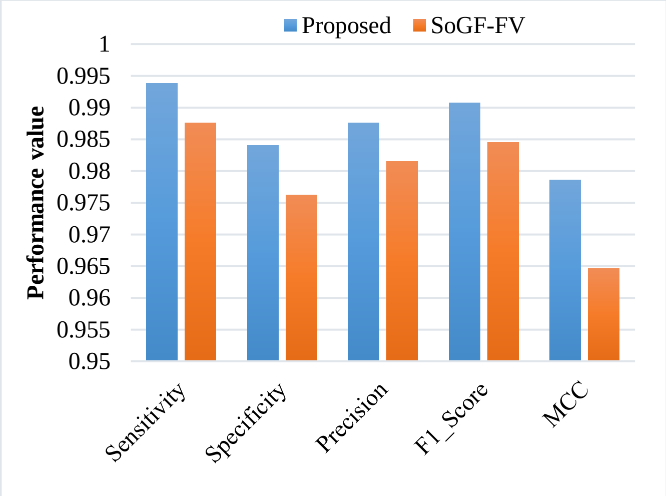

Fig 4. Performance measures

Table 1. Performance evaluation of existing and proposed techniques

Parameters	*Proposed*	*SoGF-FV*
Sensitivity	0.9964	0.9803
Specificity	0.974	0.962
Precision	0.997	0.961
F1_Score	0.99	0.98
MCC	0.97	0.96
Accuracy	0.99	0.97
Kappa Coefficient	0.97	0.961
Error rate	0.02	0.027
FPR	0.012	0.015

Fig 5 depicts the accuracy and kappa coefficients of the existing and proposed techniques. Here, the accuracy of the proposed technique is increased to 0.983 and kappa is increased to 0.981, when compared to the existing technique. Fig 6 shows the error rate and FPR of the existing and proposed techniques, where the values are efficiently reduced by the proposed FLTIP-geometrical feature extraction technique. Table 2 shows the AUC analysis of the existing and proposed techniques, where proposed technique offers an improved AUC by extracting the patterns and geometrical features in an efficient manner.

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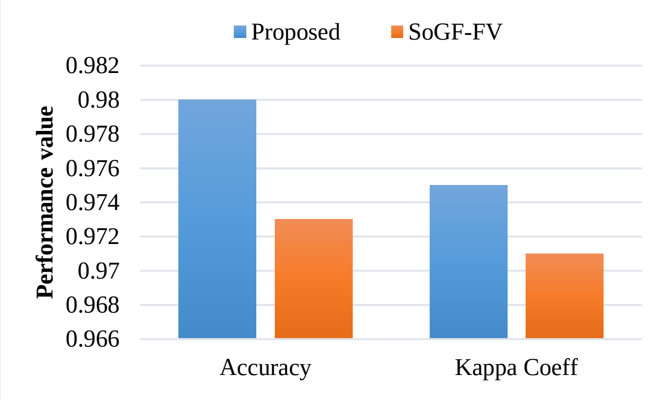

Fig 5. Accuracy and Kappa coefficients

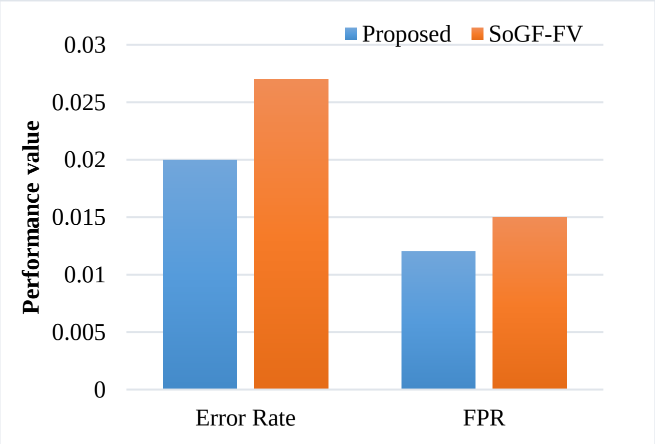

Fig 6. Error rate and FPR

Table 2. AUC analysis

Methods	*AUC*
MCC	0.6
CSM	0.57
MDC	0.86
Bayes	0.73
CS	0.92
SoGF-FV	0.92
Proposed	0.96

B. Accuracy Analysis

Table 3 evaluates the accuracy of existing and proposed classification techniques, where the proposed FLTIP-NN technique accurately classifies the hand image based on the extracted patterns and geometrical features of the input image. Moreover, the accuracy of the classifier can be determined based on its efficiency in classified label as 0 or 1. From the evaluation, it is analyzed that the proposed classification technique provides an increased accuracy, when compared to the existing techniques.

Table 3. Accuracy analysis

Methods	*Accuracy*
MCC	0.85
CSM	0.86
MDC	0.846
Bayes	0.842
CS	0.878
SoGF-FV	0.953
Proposed	0.98

C. True Positive Rate and False Positive Rate

Fig 7 shows the Receiver Operating Characteristics (ROC) of the existing and proposed techniques with respect to the values of True Positive Rate (TPR) and False Positive Rate (FPR).The FPRof classification technique is estimated bythe subtraction of specificity from the value 'one'. This analysis shows that the curve reaches the maximum sensitivity value with minimum FPR value.

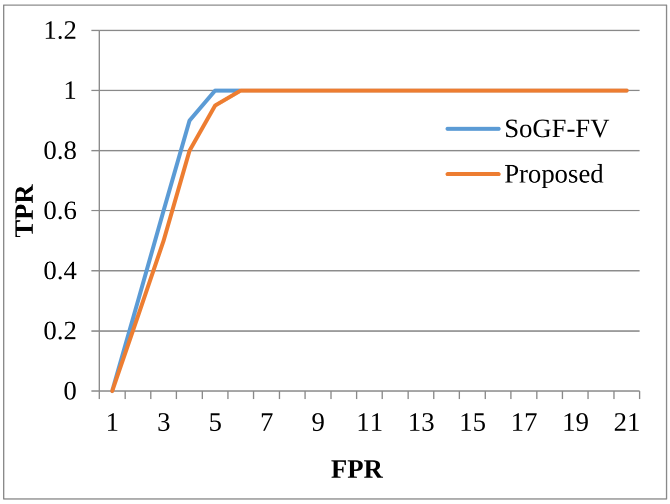

Fig 7. ROC analysis

The overall experimental analysis results depicted that the proposed FLTIP-geometric feature extraction based NN classification technique provides an improved results compared than the other techniques.

V. Conclusion

This paper proposed a new pattern extraction based classification method for hand geometry feature image authentication and recognition. For this purpose, various image processing techniques are employed in this work at the stages of preprocessing, block separation, pattern extraction, and classification. Initially, the WCGF based filtering technique is implemented to reduce the noisy pixels and to smoothen in the input image. During this process, the mask matrix is constructed in the form of 3×3 and 5×5, which ensures the reduced peak to signal noise ratio. After filtering the image, the block separation is performed to increase the overall efficiency of recognition. Here, the FLTIP technique is utilized to extract the most useful patterns by computing the intensity of the center pixel with its neighboring pixels. This type of feature extract increases the overall accuracy of the image recognition system. At last, the NN classifier is deployed to classify whether the image is authenticated or unauthenticated based on the extracted feature vectors. In this paper, an extensive simulation results have been taken for evaluating the performance of the classification system. Then, some of the existing techniques are compared with the proposed mechanism, where the results depicted that the combination of WCGF-FLTIP-NN technique outperforms the other techniques. Also, it efficiently improves the performance of classification with improved recognition rate, accuracy, and reduced error value.

In future, this work can be extended by implementing a new classification technique for hand geometry feature image authentication system.

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